P1 1170789

REÇU 21 MAI 2004
WIPO PCT

THE UNITED STATES OF AMERICA

TO ALL TO WHOM THESE PRESENTS SHALL COME:

UNITED STATES DEPARTMENT OF COMMERCE
United States Patent and Trademark Office

May 18, 2004

THIS IS TO CERTIFY THAT ANNEXED HERETO IS A TRUE COPY FROM THE RECORDS OF THE UNITED STATES PATENT AND TRADEMARK OFFICE OF THOSE PAPERS OF THE BELOW IDENTIFIED PATENT APPLICATION THAT MET THE REQUIREMENTS TO BE GRANTED A FILING DATE.

APPLICATION NUMBER: *60/456,397*
FILING DATE: *March 21, 2003*
RELATED PCT APPLICATION NUMBER: *PCT/US04/08871*

BEST AVAILABLE COPY

By Authority of the
COMMISSIONER OF PATENTS AND TRADEMARKS

T. Lawrence

T. LAWRENCE
Certifying Officer

PRIORITY DOCUMENT
SUBMITTED OR TRANSMITTED IN COMPLIANCE WITH RULE 17.1(a) OR (b)

03-24-03 60456397 - 032403

JC950 U.S. PTO 03/21/03

J1050 U.S. PTO 60/456397

IN THE UNITED STATES
PATENT AND TRADEMARK OFFICE

PROVISIONAL APPLICATION FOR PATENT pursuant to 37 CFR 1.53(b)(2)

March 21, 2003 **By Express Mail** - Label No. EU 795 386 263 US

INVENTOR

Irena MARAVIĆ, residing at Avenue du Mont d'Or 69, 1007 Lausanne, Switzerland
Martin VETTERLI, residing at Chemin de Baussan 11, 1091 Grandvaux, Switzerland

TITLE

Subspace Methods for Channel Estimation and Synchronization in Ultra-Wideband Systems

ASSISTANT COMMISSIONER FOR PATENTS - Box Provisional Application
WASHINGTON, D.C. 20231

SIR:

For the above-identified provisional application, submitted herewith is a 25-page description, a credit-card authorization form for payment of the filing fee in the amount of $80.00, and a return postcard. The applicant is entitled to Small-Entity Status.

Please address all correspondence to **Peter A. Businger, Esq., 344 Valleyscent Avenue, Scotch Plains, NJ 07076-1170**, telephone No. (908) 322-4835.

Respectfully,

Peter A. Businger

Peter A. Businger
Reg. No. 27,862
Attorney for Applicant(s)

Date: March 21, 2003

Subspace Methods for Channel Estimation and Synchronization in Ultra-Wideband Systems

Irena Maravić Martin Vetterli

IC-LCAV, Swiss Federal Institute of Technology in Lausanne, CH-1015 Lausanne, Switzerland

{Irena.Maravic, Martin.Vetterli}@epfl.ch

Abstract

We consider the problem of low-complexity channel estimation in digital ultra-wideband receivers. We extend some of our recent sampling results for certain classes of non-bandlimited signals and develop several methods that take advantage of transform techniques to estimate channel parameters from a low-dimensional subspace of a received signal, that is, by sampling the signal below the Nyquist rate. By lowering the sampling rate, we reduce computational requirements compared to current digital solutions, allow for slower A/D converters and potentially significantly reduce power consumption of digital receivers. Our approach is particularly suitable for indoor wireless sensor networks, where low rates and low power consumption are required. One application to high-resolution acquisition in ultra-wideband localizers is also presented.

Keywords

UWB, multipath channel, singular value decomposition, annihilating filters, waterfilling, filter banks, UWB localizers.

I. Introduction

Ultra-wideband (UWB) technology has recently received much attention due to benefits of exceptionally large fractional bandwidth [2] [23], such as very fine time resolution for accurate ranging, imaging and multipath fading mitigation. UWB signals are generated by driving an antenna with very short electrical pulses, typically on the order of a nanosecond, thus spreading the signal energy from near DC to a few gigahertz. Due to simplified analog front-end and duty-cycling nature of pulse-based communication, ultra-wideband technology promises much lower power consumption and higher integration than might be conventionally feasible. Although the possibility of using extremely short pulses for certain applications (such as ranging or imaging) has been investigated for at least two decades, there still remains a lot to be done for this technology to become pervasive using newly defined FCC regulations [5]. Some of the important issues that remain include low-cost and low-power designs and novel system architectures that allow for coexistence with other narrowband systems.

One of the crucial tasks of an UWB system, which imposes serious restrictions on the system performance, is synchronization. There is a vast literature that has appeared recently [2] [4] [7] [9] [11] [23], addressing both algorithmic and implementation issues of

[redacted]

several synchronization techniques, with a clear trend to eliminate as much as possible the necessity for analog components and perform all processing digitally [1] [4] [11].

While high-performance schemes have already been proposed for analog systems [6] [7], their application to digital-oriented solutions is still not feasible due to prohibitively high computational requirements. Furthermore, implementation of such techniques in digital systems would require very fast and expensive A/D converters (operating in the gigahertz range) and therefore high power consumption. And finally, they are mostly based on exhaustive search and are inherently time consuming.

We propose several frequency domain methods for channel estimation and synchronization in UWB systems, which use low-rate uniform sampling and well-developed algorithmic solutions. We extend some of our recent sampling results for certain classes of non-bandlimited signals [12] [22] to the problem of channel estimation in ultra-wideband channels and develop algorithms for estimating unknown time delays and propagation coefficients by sampling a received signal below the Nyquist rate. Our approach takes advantage of the low-rank property and the algebraic structure of the data matrix under noise-free conditions. It leads to reduced computational requirements and faster acquisition compared to proposed digital techniques, thus allowing for a practical hardware implementation and low power consumption. It is particularly suitable in applications such as precise position location or ranging, and can also be applied to other wideband systems, primarily for timing synchronization and localization purposes. We also analyze the performances of our developed schemes in the presence of noise, and discuss possible modifications of the algorithms using a filter bank approach.

II. Subspace Channel Estimation

A. Problem Statement

A number of propagation studies for ultra-wideband signals have been done, which take into account temporal properties of a channel or characterize a spatio-temporal channel response [2] [18]. A typical model for an impulse response of a multipath fading channel

[1]Digital implementation offers many advantages, such as lower power, cheaper technology, full integration, robustness etc.

is given by

$$h(t) = \sum_{l=1}^{L} a_l \delta(t - t_l) \tag{1}$$

where t_l denotes a signal delay along the l-th path while a_l is a complex propagation coefficient which includes a channel attenuation and a phase offset along the l-th path. While this model does not adequately reflect specific bandwidth-dependent effects, it provides a good characterization of the propagation channel used for diversity reception schemes (i.e. RAKE receivers). Equation (1) can be interpreted as saying that a received signal $y(t)$ is made up of a weighted sum of attenuated and delayed replicas of a transmitted signal $s(t)$, i.e.

$$y(t) = \sum_{l=1}^{L} a_l s(t - t_l) + \eta(t) \tag{2}$$

where $\eta(t)$ denotes receiver noise. Note that the received signal $y(t)$ has only $2L$ degrees of freedom, time delays t_l and propagation coefficients a_l. Although these parameters can be estimated using the time domain model (2), an efficient, closed-form solution is possible if we consider the problem in the frequency domain.

Let $Y(\omega)$ denote the Fourier transform of the received signal

$$Y(\omega) = \sum_{l=1}^{L} a_l S(\omega) e^{-j\omega t_l} + N(\omega) \tag{3}$$

where $S(\omega)$ and $N(\omega)$ are Fourier transforms of $s(t)$ and $\eta(t)$ respectively. Clearly, spectral components are given by a sum of complex exponentials, where the unknown time delays appear as complex frequencies while propagation coefficients appear as unknown weights. Thus the problem of estimating the channel parameters can be considered as a special case of classic harmonic retrieval problems, well-studied in spectral estimation literature [10]-[14]. There is a particularly attractive class of subspace or SVD-based algorithms, called super-resolution methods, which can resolve closely spaced sinusoids from a short record of noise-corrupted data. In [14] a State Space method is proposed to estimate parameters of superimposed complex exponentials in noise, while a similar ESPRIT algorithm is presented in [13]. In [10] several SVD-based techniques for estimating generalized eigenvalues of matrix pencils are addressed, which can be directly applied to our case, such as Direct Matrix Pencil Algorithm, Pro-ESPRIT and its improved version TLS-ESPRIT. Another

class of algorithms is based on the optimal maximum likelihood (ML) estimator [1]. While ML methods generally require l-dimensional search and are computationally more consuming than the SVD-based algorithms, in some specific cases they can be simplified to allow for a closed form minimization procedure. In [21] two such methods - Iterative Quadratic Maximum Likelihood (IQML) method and MODE algorithm are discussed.

In the following, we develop an algorithm based on the State Space approach [14], that provides an elegant and numerically robust tool to estimate the channel parameters from a signal subspace. In particular, we show that it is possible to solve for all the parameters from a set of samples obtained by sampling a lowpass version of the received signal. In the noiseless case, the minimum required width of the frequency band is determined by the number of degrees of freedom per unit or time (which is typically on the order of MHz), while in the noisy case it is mainly determined by a received signal-to-noise ratio. We will show that even when the signal power is well below thermal noise level, it is possible to obtain high-resolution estimates from a low-dimensional subspace. While in all derivations we will be considering the lowpass version of the signal, it is worth noting that this is not a requirement for the success of our methods, that is, the developed algorithms would work with a bandpass approximation of the signal as well.

B. Algorithm outline

Suppose that the received signal $y(t)$ is filtered with an ideal lowpass filter $H_b = \mathrm{rect}(-f_b, f_b)$ and sampled uniformly at a sub-Nyquist rate $R_s \geq 2f_b$. From the set of samples, we can compute the DFT coefficients $Y[m]$ that correspond to the lowpass version of $y(t)$. Denote by $S[m]$ the DFT coefficients of the transmitted UWB pulse and let $Y_s[m] = Y[m]/S[m]$, assuming that in the considered frequency band this division is not ill-conditioned. Define next a $P \times Q$ data matrix $\mathbf{J}$ as

$$\mathbf{J} = \begin{pmatrix} Y_s[0] & Y_s[1] & \dots & Y_s[Q-1] \\ Y_s[1] & Y_s[2] & \dots & Y_s[Q] \\ \vdots & & & \\ Y_s[P-1] & Y_s[P] & \dots & Y_s[P+Q-2] \end{pmatrix} \qquad (4)$$

If we let $P, Q \geq L$ and $z_l = e^{-j\omega_0 t_l}$, the data matrix $\mathbf{J}$ can be written as $\mathbf{J} = U\Lambda V^T$, with

matrices U, Λ, and V defined as

$$U = \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \\ z_1 & z_2 & z_3 & \dots & z_L \\ \vdots & & & & \\ z_1^{P-1} & z_2^{P-1} & z_3^{P-1} & \dots & z_L^{P-1} \end{pmatrix} \tag{5}$$

$$\Lambda = diag\,(a_1 \quad a_2 \quad a_3 \quad \dots \quad a_L) \tag{6}$$

$$V = \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \\ z_1 & z_2 & z_3 & \dots & z_L \\ \vdots & & & & \\ z_1^{Q-1} & z_2^{Q-1} & z_3^{Q-1} & \dots & z_L^{Q-1} \end{pmatrix} \tag{7}$$

The state space method is based on two properties of the data matrix $\mathbf{J}$. The first one is that in the theoretical case of noiseless data, $\mathbf{J}$ has rank L. This will allow us to reduce the noise level by approximating a noisy data matrix with an optimal, rank L matrix. The second one is the Vandermonde structure of U and V, that is, they both satisfy the so-called shift-invariant subspace property,

$$\overline{U} = \underline{U} \cdot \Phi \quad \text{and} \quad \overline{V} = \underline{V} \cdot \Phi \tag{8}$$

where Φ is a diagonal matrix having z_i's along the main diagonal, while $\overline{(\cdot)}$ and $\underline{(\cdot)}$ denote the operations of omitting the first and the last row of $(\cdot)$ respectively. Our algorithm can be thus summarized as follows:

1. Compute the spectral coefficients $Y[m]$ from the set of samples

$$y_n = < h_b(t - nT_s), y(t) >, \quad n = 1, \dots, L_1 \tag{9}$$

where $T_s = 1/R_s$ and $L_1 \geq 2L$.

2. Define a $P \times Q$ matrix $\mathbf{J}$ as

$$\mathbf{J} = \begin{pmatrix} Y_s[0] & Y_s[1] & \dots & Y_s[Q-1] \\ Y_s[1] & Y_s[2] & \dots & Y_s[Q] \\ \vdots & & & \\ Y_s[P-1] & Y_s[P] & \dots & Y_s[P+Q-1] \end{pmatrix} \tag{10}$$

where $Y_s[m] = Y[m]/S[m]$ and P and Q satisfy the following relations: $P, Q \geq L$ and $P + Q \leq L_1$.

3. Compute the singular value decomposition of $\mathbf{J}$

$$\mathbf{J} = U_s \Lambda_s V_s^H + U_n \Lambda_n V_n^H \tag{11}$$

The first term consists of L principal components, where the columns of U_s and V_s correspond to principal left and right singular vectors of $\mathbf{J}$ respectively. The second term consists of remaining nonprincipals due to noise.

4. Estimate the signal poles $z_l = e^{-j\omega_0 t_l}$ as generalized eigenvalues of the matrix pencil

$$\overline{V_s} - z\underline{V_s} \tag{12}$$

In practice, the generalized eigenvalues of (12) are estimated by computing the eigenvalues of a matrix Z, defined as

$$Z = \underline{V_s}^+ \cdot \overline{V_s} \tag{13}$$

where $(\cdot)^+$ denotes the pseudoinverse of $(\cdot)$.

5. Find the propagation coefficients a_l from the Vandermonde system

$$Y_s[m] = \sum_{l=1}^{L} a_l e^{-jm\omega_0 t_l}, \quad m \in [1, L] \tag{14}$$

Note that we have converted the nonlinear estimation problem into the simpler problem of estimating the parameters of a linear model. Nonlinearity is postponed for the last step, where in all spectral estimation methods the desired information is extracted from the estimated signal poles. Yet, the state space approach provides a lot of flexibility in model parameterization with respect to finite precision errors and sensitivity of estimated parameters to model mismatch [15].

Note that in the above algorithm we considered the lowpass approximation of the signal to estimate all the relevant parameters. In practice, however, it may be desirable to sample a bandpass version of the signal, while the best performance of our method is achieved if we choose a frequency band where the signal-to-noise ratio is highest. It is also worth

noting that it suffices to use only a portion of the signal bandwidth[2] and yet obtain high-resolution estimates of all the relevant parameters, due to the fact that the problem we consider belongs to the class of non-linear estimation problems. In Section III we will discuss possible improvements of the developed framework by sampling several bands at the same time, which can be of interest, for example, in the case of very low signal-to-noise ratios. While that approach yields better numerical performances due to the fact that almost all the signal energy can be used, it also results in increased computational requirements and complexity of the receiver.

The performance of the State Space algorithm in the low signal-to-noise ratio regime can be further improved in the following way. Since in the noiseless case $\underline{V_s}$ and $\overline{V_s}$ span the same column space, we can extract L principal components from $\underline{V_s}$ and $\overline{V_s}$ by computing the joint SVD

$$[\underline{V_s}, \overline{V_s}] = U_s \Lambda_s [V_{s1}^H, V_{s2}^H] \tag{15}$$

The signal poles $z_l = e^{-j\omega_0 t_l}$ are then estimated as generalized eigenvalues of an $L \times L$ matrix pencil $V_{s1} - zV_{s2}$. While this approach typically leads to better estimation accuracy than the original State Space algorithm, it requires that the SVD of the two matrices, **J** and $[\underline{V_s}, \overline{V_s}]$ is computed.

C. Computational Complexity and Alternative Solutions

A major computational requirement of the developed algorithm is dominated by the singular value decomposition step 3., which results in the overall computational order of $\mathcal{O}(M^3)$, where $M = max(P, Q)$. On the other hand, we are often interested in estimating the parameters of only few strongest paths, therefore, computing the full SVD of the matrix **J** is not necessary. Alternatively, we can use some simpler methods from linear algebra [3] to find principal singular vectors, which have lower computational requirements and converge very fast to the desired solution. We first give an outline of the *Power Method* that can be used to compute only one dominant right (or left) singular vector of **J**. This can be of interest for initial synchronization, specifically in applications such as ranging or positioning. Later, we present its extended version applicable to the general case of

[2]The minimum required bandwidth depends on the signal-to-noise ratio and the number of parameters to be estimated. In most cases encountered in practice, it doesn't have to exceed one third of the signal bandwidth.

estimating $M_d > 1$ principal singular vectors.

Power Method

Consider a matrix $\mathbf{F} = \mathbf{J}\mathbf{J}^H$ of size $P \times P$, and suppose that $\mathbf{F}$ is diagonizable, that is, $\Lambda^{-1}\mathbf{F}\Lambda = \mathrm{diag}(\lambda_1, \ldots, \lambda_P)$ with $\Lambda = [\mathbf{v}_1, \ldots, \mathbf{v}_P]$ and $|\lambda_1| > |\lambda_2| \geq \ldots |\lambda_P|$. Given $\mathbf{y}^{(0)}$, the *power method* produces a sequence of vectors $\mathbf{y}^{(k)}$ in the following way:

$$\mathbf{z}^{(k)} = \mathbf{F}\mathbf{y}^{(k-1)}$$

$$\mathbf{y}^{(k)} = \mathbf{z}^{(k)}/\|\mathbf{z}^{(k)}\|_2 \tag{16}$$

The method converges if λ_1 is dominant and if $\mathbf{y}^{(0)}$ has a component in the direction of the corresponding dominant eigenvector $\mathbf{v}_1$. It is easily verified that $v_1, \ldots, v_P$ are the right singular vectors of $\mathbf{J}$, therefore, once the principal singular vector v_1 has been estimated, the signal pole z_s corresponding to the strongest signal component is given by $z_s = \underline{v_1}^{+}\overline{v_1}$. A possible drawback of this method is that its convergence rate depends on $|\lambda_2/\lambda_1|$, a quantity which may be close to 1 and thus cause slow convergence. Improved versions of the algorithm which overcome this problem are discussed in [3]. Note that the power method involves only simple matrix multiplications and has the computational order of $\mathcal{O}(P^2)$.

Orthogonal Iteration

A straightforward generalization of the power method can be used to compute higher-dimensional invariant subspaces, that is, to find $M_d > 1$ dominant singular vectors. The method is typically referred to as *Orthogonal Iteration* or *Subspace Iteration* and can be summarized as follows.

Given a $P \times M_d$ matrix $\mathbf{W}^{(0)}$, the method generates a sequence of matrices $\mathbf{W}^{(k)}$ through the iteration

$$\mathbf{Z}^{(k)} = \mathbf{F}\mathbf{W}^{(k-1)} \tag{17}$$

$$\mathbf{W}^{(k)}\mathbf{R}^{(k)} = \mathbf{Z}^{(k)} \;\; (Q - R\ factorization) \tag{18}$$

The computational complexity of the method is on the order of $\mathcal{O}(P^2 M_d)$, and clearly, when $M_d = 1$ the algorithm is equivalent to the power method. In practice, $\mathbf{F}$ is first

reduced to upper Hessenberg form (that is, $\mathbf{F}$ is zero below the first subdiagonal) and the method is implemented in a simpler way that avoids explicit $Q-R$ factorization in each iteration. A more detailed discussion on this topic can be found in [3].

D. More Realistic Channel Models

We will now extend our analysis to the more complex case of a channel that takes into account certain bandwidth-dependent properties. Namely, as a result of the very large bandwidth of UWB signals, components propagating along different propagation paths undergo different frequency selective distortion and a more realistic channel model for UWB systems is of the form

$$h(t) = \sum_{l=1}^{L} a_l p_l(t - t_l) \tag{19}$$

where $p_l(t)$ are different pulse shapes that correspond to different propagation paths. In this case, the DFT coefficients of the received signal are given by

$$Y[m] = S[m] \sum_{l=1}^{L} P_l[m] a_l e^{-jm\omega_0 t_l} + N[m] \tag{20}$$

where $P_l[m]$ are now unknown coefficients. One possible way to jointly estimate the relevant channel parameters is to use an approximation of the DFT coefficients $P_l[m]$ with polynomials of degree $d \leq R-1$, i.e.

$$P_l[m] = \sum_{r=0}^{R-1} p_{l,r} m^r \tag{21}$$

Equation (20) now becomes

$$Y[m] = S[m] \sum_{l=1}^{L} a_l \sum_{r=0}^{R-1} p_{l,r} m^r e^{-jm\omega_0 t_l} + N[m] \tag{22}$$

By denoting $c_{l,r} = a_l p_{l,r}$ and $Y_s[m] = Y[m]/S[m]$, we obtain

$$Y_s[m] = \sum_{l=1}^{L} \sum_{r=0}^{R-1} c_{l,r} m^r e^{-jm\omega_0 t_l} + N[m] \tag{23}$$

Similarly to the approach discussed in Section II-B, we can form the data matrix J as in (10). However, in this case, the state space method cannot be applied since the matrices

U and V (made up of left and right singular vectors of J) no longer satisfy the shift-invariance property. We will therefore present an alternative method, based on annihilating filters, which is commonly used in error-correction coding and spectral estimation [19] [22]. The main idea behind this approach is to find the so-called annihilating filter $H(z) = \sum_{k=0}^{N} H[k]z^{-k}$ that satisfies

$$(H * Y_s)[m] = 0, \;\; \forall m \in \mathbb{Z} \tag{24}$$

A useful property of such a filter is that it has multiple roots at $z_l = e^{-j\omega_0 t_l}$ [22], that is,

$$H(z) = \prod_{l=1}^{L}(1 - e^{-j\omega_0 t_l} z^{-1})^R = \sum_{k=0}^{RL} H[k]z^{-k} \tag{25}$$

In the following, we give an outline of the algorithm, while a more detailed analysis of the annihilating filters is presented in [19] and [22].

Annihilating filter method

1. Find the coefficients $H[k]$ of the annihilating filter

$$H(z) = \prod_{l=1}^{L}(1 - e^{-j\omega_0 t_l} z^{-1})^R = \sum_{k=0}^{RL} H[k]z^{-k} \tag{26}$$

which satisfies

$$H[m] * Y_s[m] = \sum_{k=0}^{RL} H[k]Y_s[m-k] = 0, \;\; \forall m \in \mathbb{Z} \tag{27}$$

In matrix form, the system (27) is equivalent to

$$\begin{pmatrix} \vdots & \vdots & \cdots & \vdots \\ Y_s[1] & Y_s[0] & \cdots & Y_s[-(RL-1)] \\ Y_s[2] & Y_s[1] & \cdots & Y_s[-(RL-2)] \\ \vdots & \vdots & \ddots & \\ Y_s[RL] & Y_s[RL-1] & \cdots & Y_s[0] \\ \vdots & \vdots & & \end{pmatrix} \cdot \begin{pmatrix} H[0] \\ H[1] \\ \vdots \\ H[RL] \end{pmatrix} = \mathbf{0}. \tag{28}$$

Since there are $RL+1$ unknown filter coefficients, we need at least $RL+1$ equations, therefore, the number of DFT coefficients we have to compute is at least $2RL+1$. By setting $H(0) = 1$, at critical sampling (28) becomes

$$\begin{pmatrix} Y_s[0] & Y_s[-1] & \cdots & Y_s[-RL] \\ Y_s[1] & Y_s[0] & \cdots & Y_s[-(RL-1)] \\ \vdots & \vdots & \ddots & \\ Y_s[RL-1] & Y_s[RL-2] & \cdots & Y_s[0] \end{pmatrix} \cdot \begin{pmatrix} H[1] \\ \vdots \\ H[RL] \end{pmatrix} = - \begin{pmatrix} Y_s[1] \\ Y_s[2] \\ \vdots \\ Y_s[RL] \end{pmatrix} \qquad (29)$$

This systems of equations is usually referred to as the high-order Yule-Walker system [19].

2. Find the values of t_l by finding the roots of $H(z)$. Recall that $H(z)$ which satisfies (27) has multiple roots at $z_l = e^{-j\omega_0 t_l}$, that is,

$$H(z) = \prod_{l=1}^{L} (1 - e^{-j\omega_0 t_l} z^{-1})^R \qquad (30)$$

At this point it is worth noting that while this is true in the noiseless case, in the presence of noise it is more desirable to estimate the time delays from L roots of $H(z)$ which are closest to the unit circle.

3. Solve for the coefficients $c_{l,r}$ by solving the linear system of at least RL equations in (23),

$$Y_s[m] = \sum_{l=1}^{L} \sum_{r=0}^{R-1} c_{l,r} m^r e^{-jm\omega_0 t_l} \qquad (31)$$

While the above described method uses standard computational procedures, for low values of signal-to-noise ratio it should be modified since any least-square procedure that determines H directly from (29) has poor numerical precision. In practice, this problem can be dealt with by using oversampling and an SVD step, where the matrix $\mathbf{Y_s}$ is decomposed as

$$\mathbf{Y_s} = U_s \Lambda_s V_s^H + U_n \Lambda_n V_n^H \qquad (32)$$

with the first term corresponding to the best (in the Frobenius-norm sense) rank L approximation of the matrix $\mathbf{Y_s}$. The filter coefficients H are then computed as

$$H = -V_s \Lambda_s^{-1} U_s^H \cdot \begin{pmatrix} Y_s[1] \\ Y_s[2] \\ \vdots \\ Ys[RL] \end{pmatrix} \qquad (33)$$

So far we have considered only the low-dimensional subspace of the received signal, obtained by filtering the signal with a bandpass filter. A possible modification of the sampling scheme, obtained by sampling several bands and estimating the channel from a larger subspace is considered in the next section.

III. FILTER BANKS AND WATERFILLING APPROACH

As already pointed out, our framework is a frequency domain approach that allows for high-resolution estimation of channel parameters by exploiting a low-dimension property of the signal subspace. While in the noiseless case it is possible to estimate the parameters from any subspace of appropriate dimension, in the presence of noise the best performance of our algorithm is expected when the anti-aliasing filter is chosen such that a signal-to-noise ratio at its output is maximized. An alternative approach would be to use a filter bank at the receiver where each subband is sampled at a rate determined by the filter bandwidth, while the sampled signals are then combined before running the estimation algorithm. That is, the set of coefficients $Y_s[m]$ is computed for each subband separately, and then combined to form the matrix J in (10). An obvious advantage of this approach is that almost all the signal energy is used, while the power is saved by running slower A/D converters in parallel. However, this results in increased computational requirements of the estimation algorithm.

In the case when the channel parameters are estimated from adjacent subbands, the developed algorithms remain essentially the same, since J is a Hankel matrix made up of consecutive DFT coefficients $Y_s[m]$. A more interesting case, and perhaps more important in practice, is when the parameters are estimated from bands that are not necessarily adjacent. For example, if noise level in certain bands is relatively high or if some bands are subject to strong interference (such as interference from narrowband systems), it is desirable to estimate the channel by sampling only those bands where SNIR (signal-to-noise-plus-interference ratio) is relatively high. We will show that our developed algorithms can be adapted rather simply to handle this case.

Assume for simplicity that we want to estimate the parameters by sampling only two bands B_1 and B_2. Let $Y[m]$, $m \in [M_1, N_1] \cup [M_2, N_2]$, be the DFT coefficients computed from the set of samples in each band, and let $Y_s[m] = Y[m]/S[m]$ assuming again that the

above division is well-conditioned. Next construct a block-Hankel data matrix $\mathbf{J}$ as

$$\mathbf{J} = \begin{pmatrix} Y_s[M_1] & Y_s[M_1+1] & \dots & Y_s[M_1+Q-1] \\ \vdots & & & \\ Y_s[M_1+P_1-1] & Y_s[M_1+P_1] & \dots & Y_s[M_1+P_1+Q-2] \\ Y_s[M_2] & Y_s[M_2+1] & \dots & Y_s[M_2+Q-1] \\ \vdots & & & \\ Y_s[M_2+P_2-1] & Y_s[M_2+P_2] & \dots & Y_s[M_2+P_2+Q-2] \end{pmatrix} \tag{34}$$

In the noiseless case, the matrix $\mathbf{J}$ can be written as $\mathbf{J} = U\Lambda V^T$, where U, Λ, and V are now defined as

$$U = \begin{pmatrix} z_1^{M_1} & z_2^{M_1} & z_3^{M_1} & \dots & z_L^{M_1} \\ \vdots & & & & \\ z_1^{M_1+P_1-1} & z_2^{M_1+P_1-1} & z_3^{M_1+P_1-1} & \dots & z_L^{M_1+P_1-1} \\ z_1^{M_2} & z_2^{M_2} & z_3^{M_2} & \dots & z_L^{M_2} \\ \vdots & & & & \\ z_1^{M_2+P_2-1} & z_2^{M_2+P_2-1} & z_3^{M_2+P_2-1} & \dots & z_L^{M_2+P_2-1} \end{pmatrix} \tag{35}$$

$$\Lambda = diag\,(\,a_1 \quad a_2 \quad a_3 \quad \dots \quad a_L\,) \tag{36}$$

$$V = \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \\ z_1 & z_2 & z_3 & \dots & z_L \\ \vdots & & & & \\ z_1^{Q-1} & z_2^{Q-1} & z_3^{Q-1} & \dots & z_L^{Q-1} \end{pmatrix} \tag{37}$$

Clearly, the matrix V has the same Vandermonde structure as in 7), meaning that the shift-invariance property (8) holds in this case as well, that is,

$$\overline{V} = \underline{V} \cdot \Phi \tag{38}$$

where Φ is the diagonal matrix having z_i's along the main diagonal. Therefore, the signal poles can be estimated from the right singular vectors of $\mathbf{J}$, using the algorithm described in Section II-B. However, it is interesting to note that the similar approach can be used to estimate the signal poles from the left singular vectors, which is of interest, for example,

in the case when the number of rows in $\mathbf{J}$ is larger than the number of columns. Namely, the key is to observe the following property of the matrix $\mathbf{U}$

$$\overline{\overline{U}} = \underline{\underline{U}} \cdot \Phi \tag{39}$$

where $\overline{\overline{(\cdot)}}$ stands for the operation of omitting the rows 1 and $P_1 + 1$ of $(\cdot)$, and similarly, $\underline{\underline{(\cdot)}}$ denotes the operation of omitting the rows P_1 and $P_1 + P_2$ of $(\cdot)$. That is, the same shift-invariant subspace property can be exploited in this case as well, while the only modification in the developed algorithm is that the matrices $\overline{\overline{U}}$ and $\underline{\underline{U}}$ are constructed by removing the first and the last row respectively in each block of U. The same idea can be generalized to the case when we sample multiple frequency bands.

When there is additive noise, we should first extract the principal components by computing the singular value decomposition of $\mathbf{J}$

$$\mathbf{J} = U_s \Lambda_s V_s^H + U_n \Lambda_n V_n^H \tag{40}$$

and then estimate the signal poles $z_l = e^{-j\omega_0 t_l}$ as eigenvalues of a matrix Z, defined as

$$Z = \underline{V_s}^+ \cdot \overline{V_s} \tag{41}$$

or alternatively

$$Z = \underline{\underline{U_s}}^+ \cdot \overline{\overline{U_s}} \tag{42}$$

It is clear that if we are interested in estimating only the dominant left/right singular vector (or a few of them), we can also use the power method or the method of orthogonal iteration, while the signal poles are then found from (41), or alternatively (42). Also note that the annihilating filter method from Section II-D remains the same, since it doesn't rely on shift-invariance property. Namely, the only requirement is that the rows of the matrix $\mathbf{Y_s}$ in (29) are made up of consecutive coefficients $Y_s[m]$, while $\mathbf{Y_s}$ itself doesn't have to be a Hankel matrix.

IV. Rapid Acquisition in UWB localizers

One of the most interesting applications of our framework can be found in ultra-wideband transceivers intended for low-rate, low-power indoor wireless systems, for example, in systems used for precise position location. Such UWB transceivers, called localizers, have already been developed [6] and they use low duty-cycle episodic transmission

of a coded sequence of impulses to ensure low-power operation and good performance in a multipath environment. Yet, the synchronization still presents a bottleneck in the transceiver design. The system developed by *Aetherwire* [6] is analog and uses a complex method for sequence acquisition, based on the so-called Time Integrating Correlator (TIC), which implements a cascade of 32 correlators in analog circuitry and uses exhaustive search through all possible code positions. A drawback of this approach, apart from being analog, is that it is time consuming[3] since transmissions are spaced apart while the correlation window spans a small fraction of the sequence cycle time T_{cycle}. Furthermore, implementation of TIC alone can take up to 30% of the circuit area and tends to consume a major amount of the total power. An equivalent architecture based on "mostly digital" conception is proposed in [4], which consists of a simple baseband analog section followed by a large digital processing back-end, where a cascade of 128 programmable matched filters is used for synchronization purposes. This approach, however, entails all the difficulties encountered in its analog counterpart. Besides, sampling is achieved using an A/D converter designed to run at 2GHz, and developing alternative methods that would allow for simpler system architectures is still an open problem.

Our previous results can be directly extended to the case of timing synchronization (acquisition) in such systems by modeling the received signal $y(t)$ as a convolution of L delayed, possibly different, impulses with a known coding sequence $g(t)$, that is,

$$y(t) = \sum_{l=1}^{L} a_l p_l(t - t_l) * g(t) \tag{43}$$

The corresponding DFT coefficients $Y[m]$ are given by

$$Y[m] = \sum_{l=1}^{L} a_l P_l[m] G[m] e^{-jm\omega_c t_l}, \quad \omega_c = 2\pi / T_{cycle} \tag{44}$$

where $G[m]$ denote DFT coefficients of $g(t)$. If we use the polynomial approximation (21) of the spectral coefficients $P_l[m]$, the total number of degrees of freedom per one cycle is $2RL$. Therefore, the signal parameters can be estimated using low-rate uniform sampling and the method we already described in Section II-D. This potentially leads to a few orders of magnitude faster acquisition, as will be shown later.

[3]It takes approximately 1000 cycles to acquire synchronization.

V. Performance Analysis

Timing performance of our developed algorithms in UWB systems used for position location is illustrated in Figure 1 and Figure 3. All results are based on averages over 500 trials, each with a different realization of additive white Gaussian noise. We first considered the case where a coded sequence of 127 first-derivative Gaussian impulses is periodically transmitted, while a sequence duration spans approximately 20% of the cycle time T_{cycle}. Transmitted UWB pulse is illustrated in Figure 1(a), while the transmitted sequence and a received signal within one cycle are shown in Figure 1(b). We considered a possibility of "imperceptible operation", that is, we assumed that the power spectral density of a received signal is below thermal noise level. Delay estimates for the case with eight propagation paths, but one dominant (with 70% of the total power), were obtained for various values of signal-to-noise ratio (E_b/N_0) and the root-mean square errors (RMSE) of delay estimation for the dominant component is shown in Figure 1(c). We first considered the SVD-based approach and analyzed the performance of the method for different sampling rates. Our algorithm clearly yields highly accurate estimates (that is, with a sub-chip precision) for a wide range of SNRs. For example, with the sampling rate of one tenth the Nyquist rate ($N_s = N_n/10$) and $E_b/N_0 = -10dB$, the time delay along the dominant path can be estimated with an RMSE of approximately one sample[4], within only 30 cycles. Note that the main reason for using multiple cycles for estimation is to increase the effective processing gain by averaging samples taken over N_c cycles. In the same figure, we show the timing estimation performance of the algorithm based on the power method and compare the results with the Cramer-Rao Bound (CRB) [20], which represents the lowest achievable RMS error for any unbiased estimator. The two presented methods yield essentially the same RMSE, and obviously, the performance of the algorithms improves as the sampling rate increases. Note that RMSE is very close to the CRB in the case of Nyquist-rate sampling for all considered values of signal-to-noise ratio.

We next analyze the case with two dominant signal components, each containing 35%

[4]The error is expressed in terms of number of samples taken at the Nyquist rate corresponding to the received UWB signal.

of the total power, and compare the performances of the SVD-based algorithm and its simplified version that uses Orthogonal Iteration. RMSE of time delay estimation along two dominant paths versus spacing between the two components (normalized to a pulse width w) is illustrated in Figure 1(d). While, in general, sampling at one tenth of the Nyquist rate is sufficient to obtain time delay estimates with an RMSE of less than 2 samples, when the spacing between pulses is less than $2w$, higher sampling rates are required. For example, if the spacing between the two components is w, time delays can be estimated with an RMSE of approximately 1 sample, by sampling the received signal at one fifth the Nyquist rate.

In Figure 2, we show the performance of our algorithm in the case of joint pulse shape and timing estimation. A coded sequence of 127 first-derivative Gaussian impulses is periodically transmitted over a channel with two propagation paths (again assuming that the sequence time spans 20% of the cycle time), while a received (single) UWB signal is made up of two pulses of different shapes, as illustrated in Fig. 2(a). The received noiseless and noisy UWB signals for SNR=0dB are shown in Fig. 2(b). The received signal was sampled uniformly over the entire cycle at one fifth the Nyquist rate and averaged over $N_c = 60$ cycles. We used the annihilating filter method to estimate unknown time delays, by finding the roots of the annihilating filter, as well as different pulse shapes by polynomial fitting of the DFT coefficients. As already pointed out in Section II-D, the signal poles (and thus the unknown time delays) can be estimated by choosing $L = 2$ zeros closest to the unit circle. Once the time delays of the pulses have been estimated, the corresponding pulse shapes are obtained by polynomial approximation of the DFT coefficients. In this case, we used a polynomial of order $R = 20$, which clearly yields a very good approximation of the received waveforms.

In Figure 3, we show the performance of our method when the received pulse has no longer an ideal first-derivative Gaussian shape. We tested the method using a measured waveform from the propagation experiment performed at the Berkeley Wireless Research Center, illustrated in Figure 3(a). We assumed that the received signal is sampled at one tenth (or alternatively one fifth) the Nyquist rate, while the frequency band used for estimation is shown in Figure 3(b). The RMSE of delay estimation for the dominant path

vs. SNR is presented in Figure 3(c), and obviously, both the SVD approach and the power method lead to highly accurate estimates (again with a sub-chip precision). Note that with the approach based on matched filters [4], the resolution is limited by the bandwidth of the anti-aliasing filter, that is, 10 samples. Besides, the average acquisition time would be approximately five times longer, due to the fact that the method uses a combination of serial and parallel search.

Another attractive feature of our scheme is good performance in the presence of a strong narrowband interference. Namely, UWB systems must contend with a variety of interfering signals from narrowband systems and building high-Q notch filters on chip would be technically very difficult. Since our method solves the estimation problem in the frequency domain, we can simply exclude spectral components that belong to frequency bands of interfering signals, while the state space algorithm can be easily modified to handle missing blocks of data [14]. The performance of our estimator in the presence of a strong sinusoidal signal (SIR=-30dB) is illustrated in Figure 3(d).

In all the methods we presented so far, estimation is carried out by sampling the received signal uniformly over T_{cycle}. However, in the case when the sequence spans less than 10% of the cycle time, or if we are interested in estimated delays along several dominant paths, a better idea is to take a "multiresolution approach". That is, we can first obtain a rough estimate of the sequence timing, by taking uniform samples at a low rate over the entire cycle. Later, we perform precise delay estimation by increasing the sampling rate, but sampling the received signal only within a narrow window where the signal is present. This requires a "two-step" estimation, but at the same time can significantly reduce the computational requirements of the proposed schemes.

VI. Conclusion

We presented several methods for subspace parameter estimation in ultra-wideband systems, which are based on our recent sampling results for certain classes of parametric non-bandlimited signals. Our approach takes advantage of well-known spectral estimation techniques, requires much lower sampling rate and, therefore, lower complexity and power consumption compared to existing techniques. Besides, it leads to faster acquisition and allows for identification of more realistic channel models without resorting to complex

algorithms. We specifically considered the application to indoor wireless sensor networks, where low rates and low power consumption are required. The developed algorithms can be also used in other UWB applications (mainly for synchronization) as well as in other wideband systems (such as wideband CDMA).

References

[1] Y. Bresler and A. Macovski, "Exact Maximum Likelihood Parameter Estimation of Superimposed Exponential Signals in Noise", *IEEE Trans. Acoust., Speech, Signal Processing*, Vol. 34, pp. 1081-1089, Oct. 1986.

[2] R. J. Cramer, R. A. Scholtz and M. Z. Win, "Evaluation of an Ultra-Wideband Propagation Channel", *IEEE Trans. on Antennas and Propagation*, Vol. 50, No. 5, pp 561-570, May 2002.

[3] J. W. Demmel, *Applied Numerical Linear Algebra*, SIAM, Philadelphia, PA, 1997.

[4] I. O' Donnell, M. Chen, S. Wang and R. Brodersen,"An Integrated, Low-Power, Ultra-Wideband Transceiver Architecture for Low-Rate Indoor Wireless System", IEEE CAS Workshop on Wireless Communications and Networking, September 2002.

[5] FCC, *First Report and Order*, FCC 02-48, Feb. 14, 2002.

[6] R. Fleming, C. Kushner, "Spread Spectrum Localizers", U.S. Patent 5,748,891, May 5, 1998.

[7] R. Fleming, C. Kushner, G. Roberts and U. Nandiwada, "Rapid Acquisition for Ultra-Wideband Localizers", *in Proc. IEEE Conf. on UWB Systems and Technologies*, May 2002.

[8] P. Withington and L. Fullerton, "An Impluse Radio Communication System", in *Proc. of the Intl. Conf. on Ultra-Wideband, Short-Pulse Electromagnetics*, pp. 113-120, October, 1992.

[9] E. Homier and R. Scholtz, "Rapid Acquisition of UWB Signals in a Dense Multipath Channel", *in Proc. IEEE Conf. on UWB Systems and Technologies*, May 2002.

[10] Y. Hua and T. Sarkar, "On SVD for estimating Generalized Eigenvalues of Singular Matrix Pencil in Noise", *IEEE Transactions on Signal Processing*, Vol. 39, No. 4, April 1991.

[11] J. Y. Lee and R. Scholtz, "Ranging in a Dense Multipath Environment Using an UWB Radio Link", *IEEE Journal on Selected Areas in Communications*, Vol. 20, No. 9, pp. 1677-1683, December 2002.

[12] I. Maravic and M. Vetterli, "Digital DS-CDMA Receivers Working Below the Chip Rate", *In Proc. of 36-th Asilomar Conference on Signals, Systems and Computers*, November 2002.

[13] R. Roy and T. Kailath, "ESPRIT estimation of signal parameters via rotational invariance techniques", *IEEE Trans. on Acoustics, Speech and Signal Processing*, vol. 37, No.7, pp. 984-995, July 1989.

[14] B. D. Rao and K. S. Arun, "Model Based processing of Signals: A State Space Approach", *Proceedings of the IEEE*, Vol. 80, No. 2, pp. 283-309, February 1992.

[15] B. Rao, "Sensitivity analysis of state space methods in spectral estimation", in *Proc. IEEE ICASSP*, April 1987.

[16] R. A. Scholtz, "Multiple access with time-hopping impulse modulation", in *Proc. Milcom.*, Oct. 1993.

[17] U. J. Schwarz, "Mathematical-statistical Description of the Iterative Beam Removing Technique (Method CLEAN)", *Astronomy and Astrophysics*, vol. 65, pp. 345-356, 1978.

[18] Q. Spencer, M. Rice, B. Jeffs, M. Jensen, "A Statistical Model for the Angle-of-Arrival in Indoor Multipath Propagation", *in Proc. IEEE Vehicular Technology Conference*, pp. 1415-1419, 1997.

[19] P. Stoica and R. Moses, *Introduction to Spectral Analysis*, Prentice Hall, 2000.

[20] P. Stoica and A. Nehorai, "MUSIC, Maximum Likelihood and Cramer-Rao Bound", *IEEE Trans. on Acoustics, Speech and Signal Processing*, vol. 37, No.5, pp. 720-741, May 1989.

[21] A. L. Swindlehurst, "Time Delay and Spatial Signature Estimation Using Known Asynchronous Signals", *IEEE Trans. on Signal Processing*, Vol. 46, No. 2, pp. 449-462, February 1998.

[22] M. Vetterli, P. Marziliano and T. Blu, "Sampling signals with finite rate of innovation", *IEEE Transactions on Signal Processing*, vol. 50. No. 6, pp. 1417-1428, June 2002.

[23] M. Z. Win, R. A. Scholtz, "Impulse Radio: How it works", *IEEE Commun. Letters*, February 1998.

Claims

1. A method for estimating impulse response of a wideband communications channel as

sum {k from 1 to L} a(k) delta(t-t(k))

from a received ultra-wideband signal, filtered with a lowpass/bandpass filter and sampled uniformly at a sub-Nyquist rate, comprising:

(a) determining discrete-Fourier-transform coefficients y(j) and s(j) from the sampled signal and a transmitted ultra-wide-band pulse, respectively,

(b) determining dominant singular vectors of a matrix having y(j+i-1)/s(j+i-1) as its i,j-elements;

(c) estimating signal poles from the dominant singular vectors and determining the time delays t(k) from the estimated poles;

(d) determining the propagation coefficients a(k) from a Vandermonde system

y(m)/s(m) = sum {k from 1 to L} a(k) y(k)^m (for m from 1 to L).

2. The method of claim 1, wherein L is chosen as the number of dominant singular vectors in step (b).

3. The method of claim 1, wherein L is chosen as less than the number of dominant singular vectors in step (b).

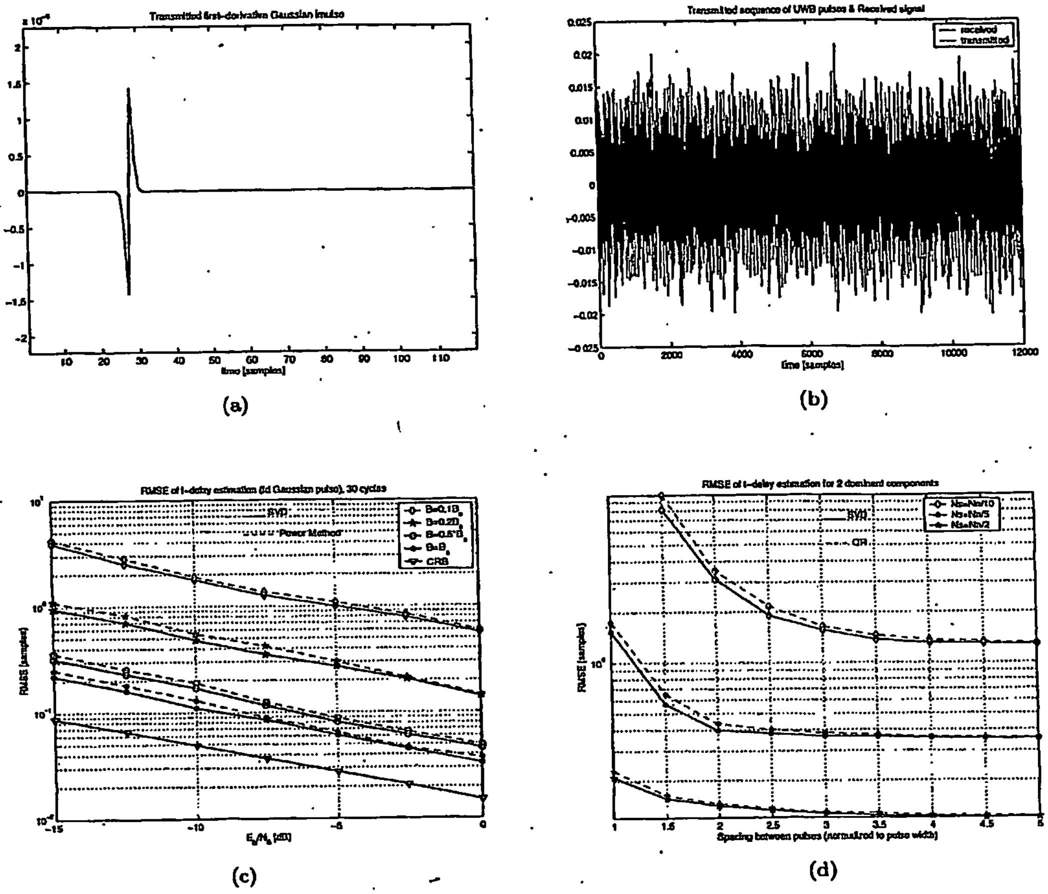

Fig. 1. Timing recovery in UWB systems (a) *Transmitted first-derivative Gaussian impulse* **(b)** *Transmitted sequence of 127 UWB impulses (red) and received signal within one cycle (blue). Received signal-to-noise ratio is $E_b/N_0 = -15dB$. Coding is achieved with a PN sequence of length 127, while the spacing between pulses (chips in the PN sequence) is assumed to be 20 samples.* **(c)** *Root-mean square errors (RMSE) of delay estimation (in terms of number of samples) vs. SNR for the case with one dominant path and for different values of the sampling rate. We assumed that the samples of the received signal are averaged over $N_c = 30$ cycles. Estimation performances of an SVD-based algorithm and its simplified version using the power method are compared with the Cramer-Rao Bound* **(d)** *RMSE of delay estimation for the case with two dominant signal components vs. spacing between received pulses. The spacing is normalized to the pulse width.*

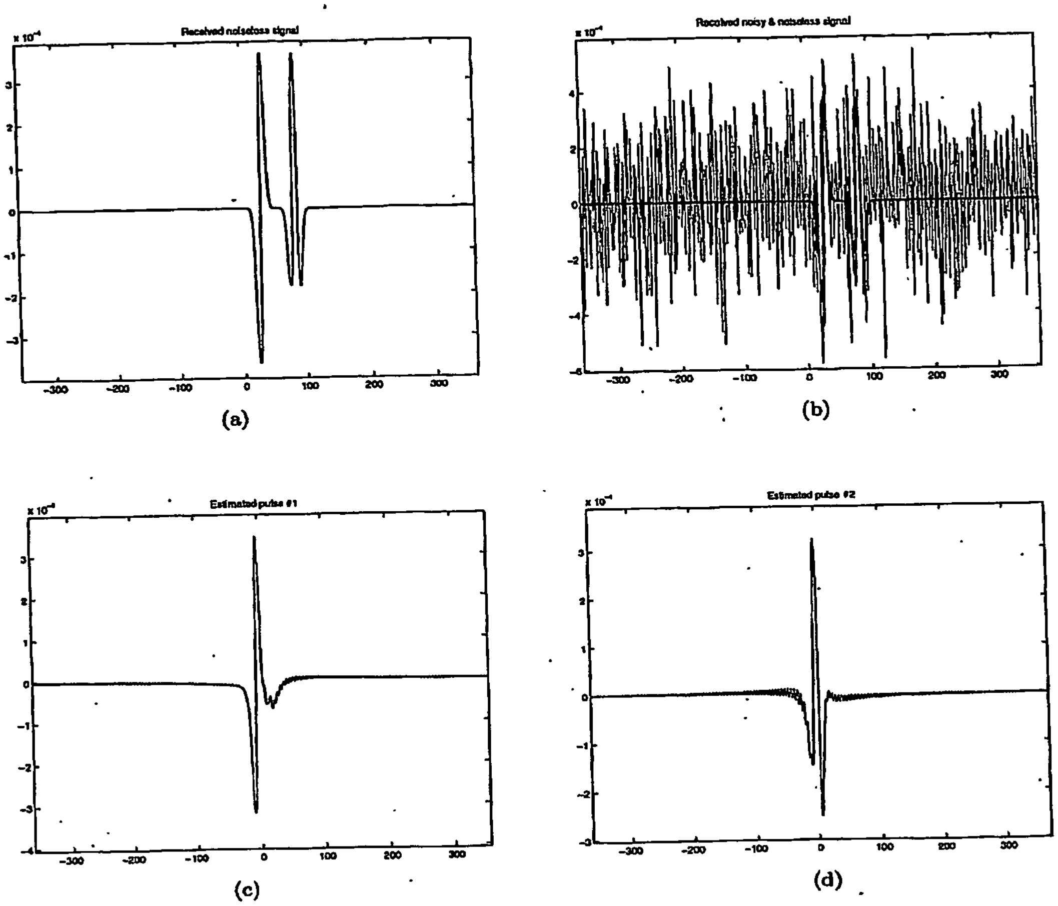

Fig. 2. **Joint pulse shape and delay estimation (a)** *Received noiseless signal made up of two short pulses having different shapes* **(b)** *Received noisy signal (blue) and the noiseless pulses (blue).* **(c)** *Estimated shape of the first pulse.* **(d)** *Estimated shape of the second pulse. In both cases, we used a polynomial of order* $R = 20$. *to approximate the DFT coefficients of the received signal.*

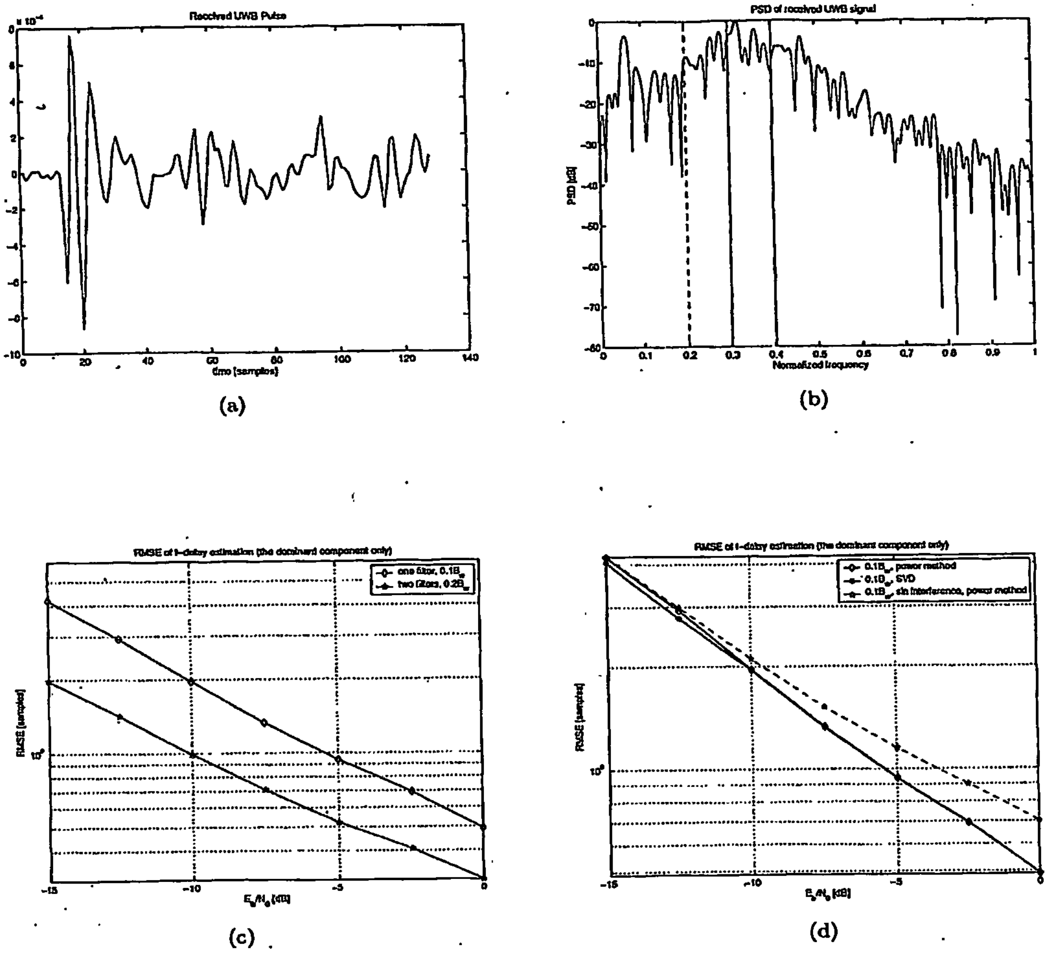

Fig. 3. **(a)** *Received pulse waveform (including multipaths) and assumed transmitted pulse shape.* **(b)** *Normalized power spectral density (PSD) of the received pulse. We used one tenth or one fifth of the signal bandwidth for estimation, as indicated with dashed lines.* **(c)** *RMSE of delay estimation vs. SNR for the dominant path. We assumed that the samples of the received signal are averaged over $N_c = 30$ cycles, and compared the performance of algorithms with SVD and the power method.* **(d)** *Estimation performance in the presence of a strong sinusoidal interference, $SIR = -30dB$.*

This Page is inserted by IFW Indexing and Scanning Operations and is not part of the Official Record

BEST AVAILABLE IMAGES

Defective images within this document are accurate representations of the original documents submitted by the applicant.

Defects in the images include but are not limited to the items checked:

- ☑ BLACK BORDERS
- ☑ IMAGE CUT OFF AT TOP, BOTTOM OR SIDES
- ☑ FADED TEXT OR DRAWING
- ☐ BLURED OR ILLEGIBLE TEXT OR DRAWING
- ☐ SKEWED/SLANTED IMAGES
- ☑ COLORED OR BLACK AND WHITE PHOTOGRAPHS
- ☐ GRAY SCALE DOCUMENTS
- ☐ LINES OR MARKS ON ORIGINAL DOCUMENT
- ☐ REPERENCE(S) OR EXHIBIT(S) SUBMITTED ARE POOR QUALITY
- ☐ OTHER: ______________________

IMAGES ARE BEST AVAILABLE COPY.
As rescanning documents *will not* correct images problems checked, please do not report the problems to the IFW Image Problem Mailbox